ACVM - 4. Assignment - Advanced tracking

Nejc Ločičnik, 63180183, nl4952@student.uni-lj.si

I. Introduction

In this assignment, we delve into motion models, Kalman filters and tracking with Particle filters. The implementation follows what we discussed during lectures and whats in the assignment slides. We test the results of Kalman filter with different motion models on different shapes (spiral, square and random). We discuss the tracking results of a particle filter based tracker, how different motion models performed, how the q parameter was set, how different amount of particles and different color spaces effected performance. The evaluation was performed on the VOT14 sequences.

II. Experiments

A. Motion Models and Kalman filter

Figure 1 shows that the motion models for RW, NCV and NCA I've implemented align with what was shown on the slides. Figures 2 and 3 show additional examples with sharper corners. This sufficiently shows how different motion models handle different movement. We can also see how heavily the results rely on the parameters q and r. The matrices for the motion models are in the appendix at the end.

Due to the random nature of RW's velocity updates, RW struggles to maintain its trejectory around sharp corners. NCV on the other hand is quite smooth with them (best seen for the square and random shape). This is because it assumes constant velocity, meaning it may underestimate the object's acceleration when approaching or departing from sharp corners, leading to slight deviations from the true path. NCA is the best at adapting to sharp corners. Incorporating acceleration changes makes it the better equipped to handle abrupt changes in motion. This is best seen in the random shape as it deviates off the path the least.

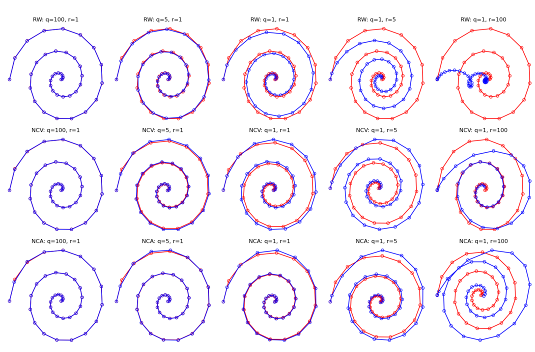

Figure 1. Recreation of the motion model spirals from the assignment slides.

B. Tracking with Particle filters

The results for tracking with particle filters vary quite a bit. For example for the sequence *hand1* you can expect 2 to 7 failures with the same settings (which makes final result evaluation annoying). This is because we have a certain degree of randomness with how the particles are sampled and moved.

To better evaluate what's going on during tracking I added circles which show the position and weight of each particle. An example of the visualization is shown in figure 4. We can clearly see when the tracker is less confident as the particles spread out a bit and their weight reduces (they become transparent).

Results of tracking with particle filters is shown in table 1 (second page). The best results were obtained with RW motion model, q=1.5, 40 particles, update parameter $\alpha = 0.07$ and $\sigma = 0.12$. σ determines how much we differentiate between small differences in the Hellinger distance (it's whats used to transform particle patch similarity to particle weights).

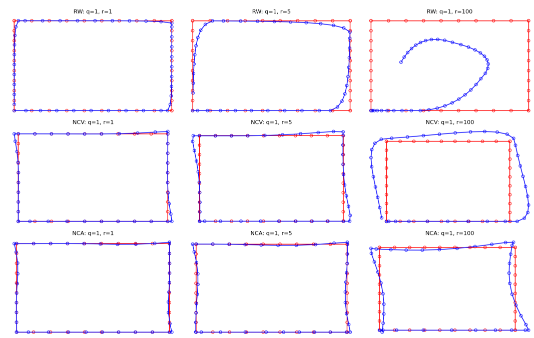

Figure 2. Kalman filter on a square shape.

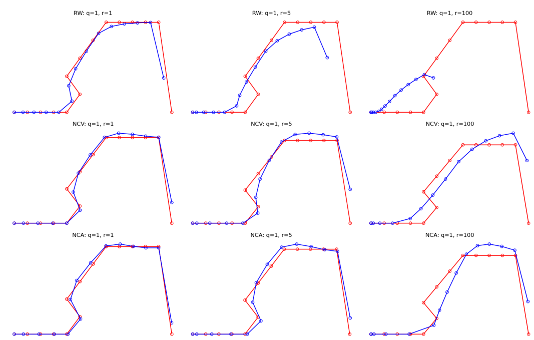

Figure 3. Kalman filter on a random shape.

C. Results of different motion models

NCV and RW motion models performed better (around 50 failures, overlap around 0.5), while NCA struggled (around 60+ failures, 0.45 overlap). I think this is mostly because none of the sequences demonstrate nearly constant acceleration, while tracking objects that are not moving or with constant velocity are commonly seen in the evaluated sequences. Objects don't need to actually stand still to appear as not moving, they can simply move with the camera movement, appearing still.

D. Parameter q

Parameter q scales the covariance matrix Q which is used for adding noise (the randomness). We want the particles to spread out within the bounding box for the tracker to function properly (cover all potential movement, according to the motion model). To achieve this we need to scale the parameter q with the size of the bounding box. I did this according to this:

$$q \cdot min(width, height) \cdot Q$$

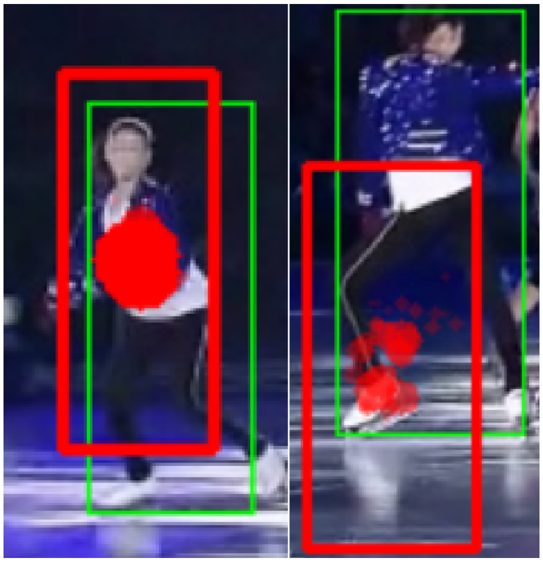

Figure 4. Visualization of particle location and weight.

Sequence	Overlap	Failures	FPS
ball	0.70	0	83.52
basketball	0.67	2	29.78
bicycle	0.38	1	93.05
bolt	0.57	2	53.04
car	0.34	0	83.69
david	0.46	1	51.86
diving	0.36	0	62.07
drunk	0.37	0	47.73
fernando	0.42	0	19.14
fish1	0.44	6	80.88
fish2	0.41	5	50.65
gymnastics	0.58	0	70.14
hand1	0.45	4	81.49
hand2	0.50	1	81.55
jogging	0.60	2	72.67
motocross	0.43	5	29.88
polarbear	0.62	0	61.20
skating	0.51	5	45.62
sphere	0.64	1	50.95
sunshade	0.54	0	73.36
surfing	0.49	1	90.59
torus	0.64	0	83.24
trellis	0.46	2	72.78
tunnel	0.35	4	81.55
woman	0.54	5	77.30
Summarized	0.50	47	65.11

Table I

Evaluation results per sequence

, with q usually ranging from 0.9 to 1.5.

E. Number of particles

Increasing the number of particles reduces the randomness, which increases repeatability. If there is enough of them, they sufficiently cover all possible movements. If there isn't enough of them, we might get unlucky where they all get sampled on one side of the distribution which might make the tracker stray from the target. If there is too many of them, the tracker will become less responsive to fast movement as the particles will be heavily repeated towards the center of the previous time step.

Obviously increasing the amount of particles also increases the amount of computation, which slows down the tracker. I found 40 to 50 to be the best performing amount of particles. Increasing or decreasing the amount decreased accuracy and robustness.

F. Different color spaces

I additionally tried different color spaces. HSV was the best performer and it's what I used most of the time. BGR (cv2 default) and RGB are obviously the same, just swapped axis. They performed slightly worse compared to HSV. Lab and YCrCb performed a lot worse (+10 fails at least).

III. Conclusion

In this assignment, we delved into advanced tracking methods, experimenting with motion models, Kalman filters, and particle filters. Through our exploration, we gained insights into how different motion models, such as Random Walk, Near-Constant Velocity, and Near-Constant Acceleration, influence tracking performance. We observed the impact of parameters like q and r on Kalman filter results and explored the nuances of particle filter-based tracking, adjusting parameters such as the number of particles, parameter q, the motion model and color spaces to optimize performance. By understanding these methods' intricacies and conducting thorough evaluations on various sequences, we gained valuable insights into addressing real-world tracking challenges effectively.

Appendix

A. Random Walk motion model matrices

In our case $T = 1$. This was derived using sympy.

$$x = [x, y]\,, F = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, A = \Phi = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$L = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, Q = q \begin{bmatrix} T & 0 \\ 0 & T \end{bmatrix}, H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

B. Near-Constant Velocity motion model matrices

In our case $T = 1$. This was derived using sympy.

$$x = [x, y, v_x, v_y]$$

$$F = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, A = \Phi = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$L = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}, Q = q \begin{bmatrix} \frac{T^3}{3} & 0 & \frac{T^2}{2} & 0 \\ 0 & \frac{T^3}{3} & 0 & \frac{T^2}{2} \\ \frac{T^2}{2} & 0 & T & 0 \\ 0 & \frac{T^2}{2} & 0 & T \end{bmatrix}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

C. Near-Constant Acceleration motion model matrices

In our case $T = 1$. This was derived using sympy.

$$x = [x, y, v_x, v_y, a_x, a_y]$$

$$F = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$A = \Phi = \begin{bmatrix} 1 & 0 & T & 0 & \frac{T^2}{2} & 0 \\ 0 & 1 & 0 & T & 0 & \frac{T^2}{2} \\ 0 & 0 & 1 & 0 & T & 0 \\ 0 & 0 & 0 & 1 & 0 & T \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, L = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$Q = \begin{bmatrix} \frac{T^5 q}{20} & 0 & \frac{T^4 q}{8} & 0 & \frac{T^3 q}{6} & 0 \\ 0 & \frac{T^5 q}{20} & 0 & \frac{T^4 q}{8} & 0 & \frac{T^3 q}{6} \\ \frac{T^4 q}{8} & 0 & \frac{T^3 q}{3} & 0 & \frac{T^2 q}{2} & 0 \\ 0 & \frac{T^4 q}{8} & 0 & \frac{T^3 q}{3} & 0 & \frac{T^2 q}{2} \\ \frac{T^3 q}{6} & 0 & \frac{T^2 q}{2} & 0 & Tq & 0 \\ 0 & \frac{T^3 q}{6} & 0 & \frac{T^2 q}{2} & 0 & Tq \end{bmatrix}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$